

ENHANCEMENT OF R-WAVE DETECTION IN ECG DATA ANALYSIS USING HIGHER-ORDER STATISTICS

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Abstract – A new way of detecting R-wave in QRS complex of electrocardiogram (ECG) based on higher-order statistics (HOS) is presented in this paper. The proposed method employs HOS-based parameters, such as skewness and kurtosis, in order to formulate an adaptive detector of R peak with high accuracy. Experimental results, when applying the proposed method to pre-classified ECG data from the Massachusetts Institute of Technology/Beth Israel Hospital (MIT/BIH) ECG database, prove that the proposed method exhibits over 99% of detectability, even when the ECG data are contaminated with noise. Due to its simplicity it could be feasible in a real-time context and it could be applied in routine ambulatory and/or clinical heart rate screening.

Keywords – Massachusetts Institute of Technology/Beth Israel Hospital (MIT/BIH) ECG database, QRS complex, skewness, kurtosis, adaptive robust detector, heart rate screening.

I. INTRODUCTION

ONE of the difficult tasks in the analysis of electrocardiogram (ECG) signal is the accurate detection of the R-wave in the QRS complex. This is due to the difficulties imposed by the time-varying morphology of ECG, the physiological variations due to the patient and the noise contamination. The latter includes power line interface, muscle contraction noise, poor electrode contact, patient movement, and baseline wandering due to respiration [1].

In most QRS detectors, the ECG signal is first bandpass filtered to reduce noise and differentiated to emphasize the large slope of R-wave. Then, a short-time energy detector is developed using a sliding analysis window [2]. Unfortunately, these detectors do not accurately account for the inherent time-varying morphology of the QRS complex. In order to overcome this problem, an adaptive technique that captures the variations in QRS is introduced in this paper, based on higher-order statistics (HOS) [3]. The property of HOS to be zero for Gaussian signals and exhibit high values for transient non-Gaussian ones provides the motivation for our approach. In particular, adaptive thresholds structured on the variation of skewness and kurtosis parameters when the QRS complex is present provide the necessary information, regarding the location of R-wave, resulting in accurate estimates. Tests of the algorithm on the Massachusetts Institute of Technology/Beth Israel Hospital (MIT/BIH) ECG database [4], prove its high performance, even in the presence of noise.

II. HOS PARAMETERS: SKEWNESS & KURTOSIS

If $\{X(k)\}$, $k = 0, \pm 1, \pm 2, \dots$ is a real stationary random process and its moments up to n order exists they could be written as

$$m_n^x(\tau_1, \tau_2, \dots, \tau_{n-1}) \equiv E\{X(k) \cdot X(k + \tau_1) \cdots X(k + \tau_{n-1})\}, \quad (1)$$

and, due to stationarity, they depend only on the time differences $\tau_1, \tau_2, \dots, \tau_{n-1}, \tau_i = 0, \pm 1, \dots$ for all i ; $E\{\cdot\}$ denotes the expected value. For $n = 3, 4$ and by putting $\tau_1 = \tau_2 = \tau_3 = 0$ (assuming that $m_1^x = 0$), the skewness γ_3^x and kurtosis γ_4^x are given by [3]:

$$\gamma_3^x = E\{X^3(k)\}, \quad (2)$$

$$\gamma_4^x = E\{X^4(k)\} - 3[E\{X^2(k)\}]^2. \quad (3)$$

In practice, for a real stationary signal $X(k), k = 1, \dots, N$, γ_3^x and γ_4^x could be estimated by

$$\hat{\gamma}_3 = \frac{\sum_{i=1}^N (x(i) - \hat{m})^3}{(N-1)\hat{\sigma}^3}, \quad (4)$$

$$\hat{\gamma}_4 = \frac{\sum_{i=1}^N (x(i) - \hat{m})^4}{(N-1)\hat{\sigma}^4} - 3, \quad (5)$$

where, \hat{m} and $\hat{\sigma}$ are the estimated mean value and standard deviation of $X(k)$, respectively.

When the $X(k)$ signal includes transients with high amplitude its distribution shifts to a non-Gaussian one. Consequently, skewness and kurtosis exhibit high values, since they express the symmetry and the heaviness of the tail of the distribution, respectively. In this way, skewness and kurtosis could be used as indices of the presence or not of a transient in the $X(k)$ signal.

III. DESCRIPTION OF THE ALGORITHM

Motivated by the abovementioned property of skewness and kurtosis we designed our approach. The block diagram of the proposed algorithm, namely HOS-based R-Wave Detector (HOS-RWD), is depicted in Fig. 1. Initially, a signal conditioning process takes place where amplitude normalization and DC extraction, using a high pass filter (5th-order Butterworth, cut-off frequency=3Hz) of the N -sampled ECG signal $x(k)$ are performed. Then, the length M ($\ll N$) of a sliding window along with the R-wave length, D , are set in accordance to the sampling frequency, f_s , as the integer part of $M=f_s/3$ and $D=0.02 \cdot f_s$, respectively. In addition, initial values of the thresholds used for the HOS parameters are also selected. Next, $x(k)$ is windowed with a 99% overlap sliding window of M samples. At each window, $\hat{\gamma}_3$ and $\hat{\gamma}_4$ are estimated using (4) and (5) and their values are located at the end of the window. Then, the local maxima of the first

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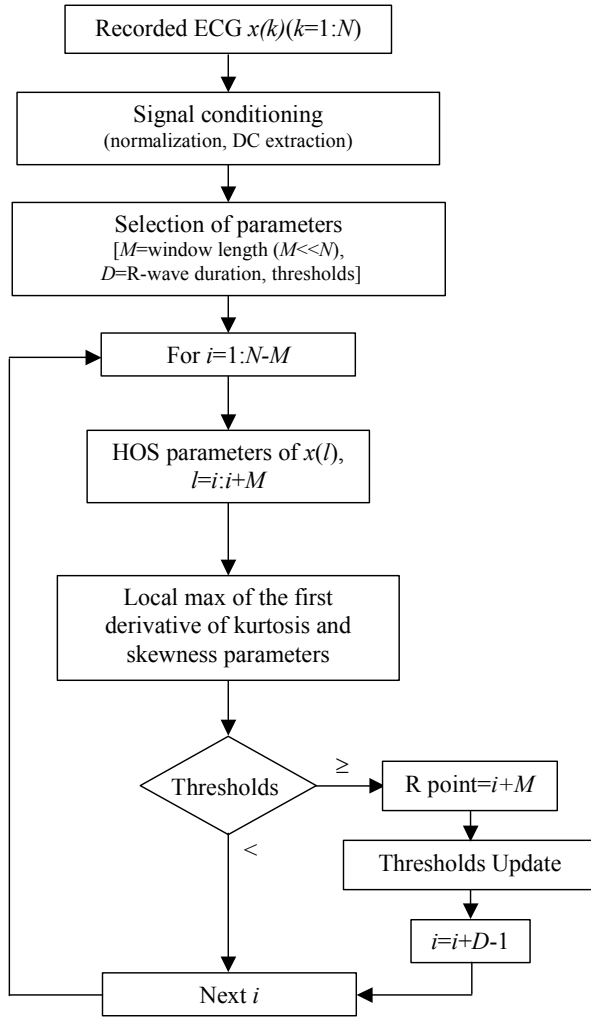


Fig. 1. Block diagram of the HOS-RWD algorithm.

derivative of $\hat{\gamma}_3$ and $\hat{\gamma}_4$ are calculated indicating the locations of possible R-wave. Subsequently, the values of $\hat{\gamma}_3$ and $\hat{\gamma}_4$ at the possible locations are compared with two thresholds; in case they are smaller we slide the window by one sample. If their values exceed the thresholds, the two locations are compared each other and in case they differ the location pointed out by kurtosis is preferred, since, unlike third-order statistics, the fourth-order statistics are not equal to zero for symmetrical distributed non Gaussian random processes [3]. Then, the thresholds are updated using the mean value of the last five maximum values of $\hat{\gamma}_3$ and $\hat{\gamma}_4$, respectively. After the estimation of the first R-wave, the window skips D samples to the right and proceeds with the next one until the end of the input data is reached.

An example of the aforementioned procedure when applied on a 1600-sample ECG section from an archive from the MIT/BIH ECG database ('100.dat') is shown in Fig. 2.

IV. IMPLEMENTATION

The whole analysis was implemented on an IBM-PC (Pentium III/800 MHz) using the programming language

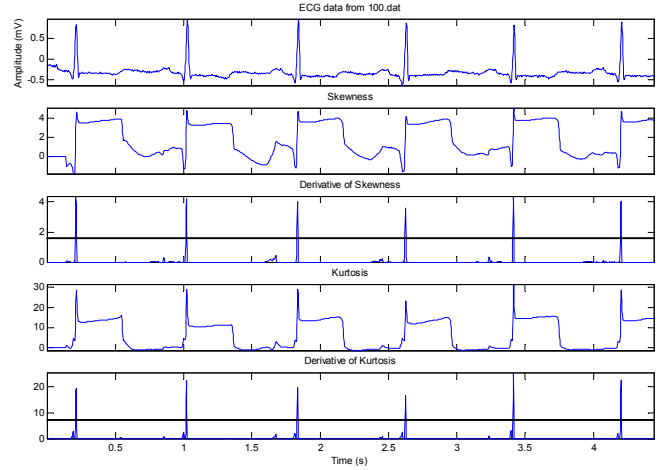


Fig. 2. Results from intermediate steps of the HOS-RWD algorithm when applied on a 1600-sample ECG section from the '100.dat' archive of the MIT/BIH ECG database. The horizontal line corresponds to thresholds.

Matlab 5.3 (The Mathworks, Inc., Natick, MA). The HOS-RWD was applied on the archives from the MIT/BIH ECG database (channel 1) presented in Table I. All analyzed files were thirty minutes long and were sampled with a sampling frequency of $f_s=360$ Hz. The values for the sliding window length and the R-wave duration were selected as $M=120$ and $D=7$ samples, respectively.

V. RESULTS AND DISCUSSION

Several examples of analysis results are shown in Figs. 3-6. In all these figures a long dashed line and a short solid one mark the locations of R-waves when identified by the cardiologists and the HOS-RWD, respectively. The R-waves identified by the cardiologists were considered as the correct ones and were used for qualitative and quantitative evaluation of the performance of the HOS-RWD.

Fig. 3 depicts a section from file '101.dat', which clearly notates a baseline wandering in ECG recordings. From the comparison of the location of the solid and dashed lines it is clear that the HOS-RWD overcomes the effect of the baseline wandering and accurately finds the true locations of R-waves.

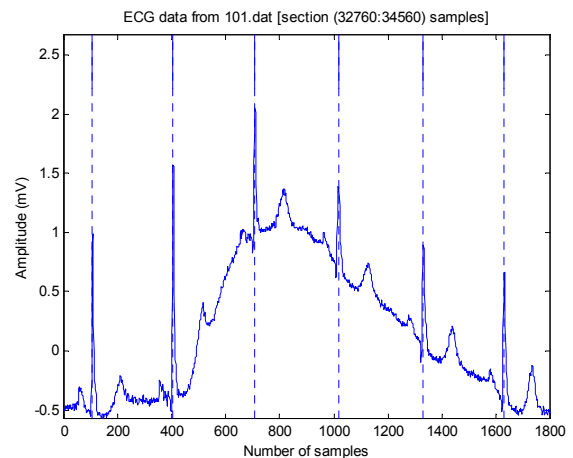


Fig. 3. ECG data from MIT/BIH ECG database, file '101.dat', section 32760:34560 samples. The vertical dashed lines indicate the cardiologists' estimate of the R-wave locations and tic marks (short solid lines) indicate the HOS-RWD estimate of the R-wave locations.

Fig. 4 includes a section from file '107.dat' and illustrates a case of ECG with a deep S-wave in the QRS complex. In this case there is always the risk of misidentification of the true location of the R-wave due to the sharp S-wave peak. By careful examination of the location of the solid and dashed lines it is clear that the cardiologists' identification of the R-wave locations is slightly shifted to the right of the R-wave peaks. On the contrary, the HOS-RWD's identification of the R-wave locations coincides with the location of the R-wave peaks, independently from the presence of deep S-waves. Thus, in this case, the R-waves identified by the HOS-RWD, despite their difference (by one or two samples) from the ones identified by the cardiologists, where considered as the correct ones.

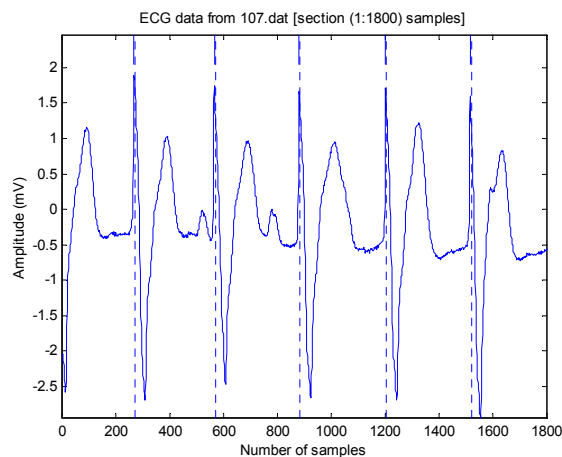


Fig. 4. ECG data from MIT/BIH ECG database, file '107.dat', section 1:1800 samples. The vertical dashed lines indicate the cardiologists' estimate of the R-wave locations and tic marks (short solid lines) indicate the HOS-RWD estimate of the R-wave locations.

Fig. 5 shows a section from file '118.dat' where two arrhythmia episodes are present (3rd and 6th QRS complexes) along with deep S-waves. Similarly to the previous cases, when comparing the location of the solid and dashed lines it is clear that the HOS-RWD overcomes the arrhythmia effect and accurately identifies the true locations of R-waves.

Fig. 6(a) illustrates a noisy ECG recording, taken from another part of file '118.dat', where apart from the existence of deep S-waves there is a noise contamination. The noise presence results in a sequence of further deteriorated QRS complexes. Despite the simultaneous presence of the aforementioned factors, the HOS-RWD still clearly identifies the true location of R-waves, since the location of the dashed and solid lines are identical in all cases but the 8th. With a close examination of that peak, by employing its zoomed version shown in Fig. 6(b), it is clear that the cardiologists' location of the R-wave is not correct, since it coincides with the location of the deep S-wave. In contrast, the one found by the HOS-RWD points out the correct position of the R-wave, despite the presence of both deep S-wave and noise. The latter is due to the property of skewness and kurtosis to become equal to zero for Gaussian distributed random processes, such as additive Gaussian noise [3].

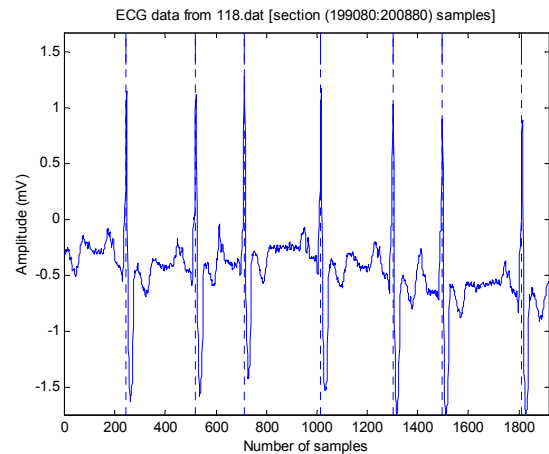
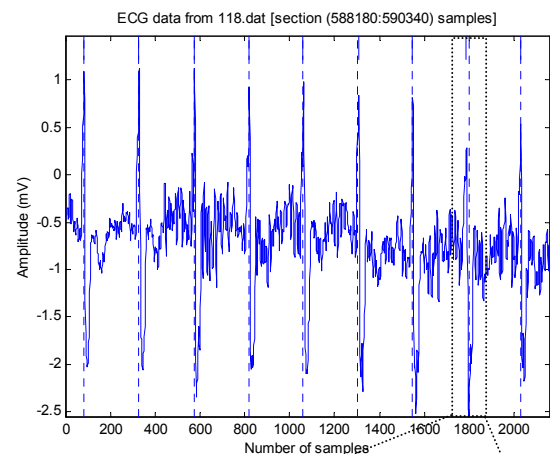
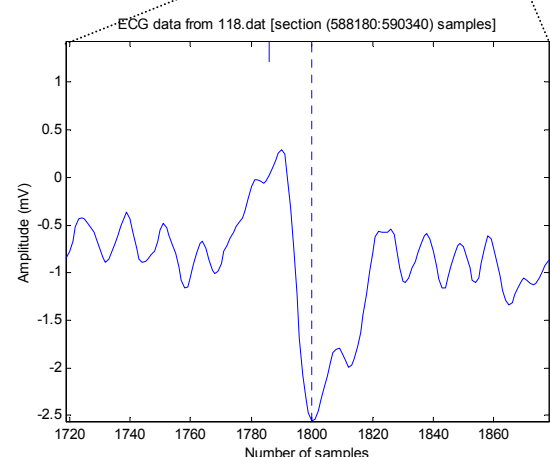


Fig. 5. ECG data from MIT/BIH ECG database, file '118.dat', section 199080:200880 samples. The vertical dashed lines indicate the cardiologists' estimate of the R-wave locations and tic marks (short solid lines) indicate the HOS-RWD estimate of the R-wave locations.



(a)



(b)

Fig. 6. (a) ECG data from MIT/BIH ECG database, file '118.dat', section 588180:590340 samples. (b) A zoomed version of the 8th QRS complex from the ECG data depicted in (a). The vertical dashed lines indicate the cardiologists' estimate of the R-wave locations and tic marks (short solid lines) indicate the HOS-RWD estimate of the R-wave locations.

TABLE I
PERFORMANCE OF THE HOS-RWD ALGORITHM WHEN APPLIED ON FILES
(CHANNEL 1) FROM THE MIT/BIH ECG DATABASE

File Name	Record Duration (min)	Total number of identified R-waves		D_R (%)	TD_R (%)
		Cardiologists	HOS-RWD		
		N_R	N_E		
100.dat	30	2272	2272	100	
101.dat	30	1863	1863	100	
103.dat	30	2084	2084	100	99.91
107.dat	30	2078	2077	99.95	\pm
118.dat	30	2278	2268	99.56	0.17
201.dat	30	2145	2145	100	

^a Standard deviation of TD_R

Apart from the qualitative evaluation of the results by visual examination of Figs. 3-6, a quantitative analysis was also performed. For the quantitative evaluation of the efficiency of the HOS-RWD, the following quantitative evaluators were calculated, defined by Hadjileontiadis and Panas [5], i.e.,

Rate of Detectability (%):

$$D_R = \left(1 - \frac{N_R - N_E}{N_R} \right) \cdot 100, \quad (6)$$

and

$$\text{Total Performance (\%): } TD_R = \text{mean}(D_R), \quad (7)$$

where, N_R denotes the number of R-waves identified by the cardiologists and N_E the number of R-waves identified by the HOS RWD.

The quantitative evaluators in (6) and (7) describe the ability of the HOS-RWD to find the correct number of R-waves at the correct position in the raw data. Analytical results for the quantitative evaluators for each case are shown in Table I. These results indicate a very efficient performance of the HOS-RWD, since it exhibits a total detectability of almost 100%.

From the above results, it can be seen that the proposed approach overcomes the limitations seen in previous methods, described in detail in [1], [2], when using fixed duration windowing techniques in detecting time-varying transients. Although a fixed duration sliding window is also used in the present study, the spectral/temporal variations in QRS morphology are captured by the properties of the employed HOS parameters, eliminating any trade off between the window duration and false and missed detections. In addition, the elimination of Gaussian noise in the HOS domain increases the robustness of the HOS-RWD algorithm, resulting in accurate R-wave detections even in the presence of noise in ECG recordings.

Regarding the computational cost of the HOS-RWD the average execution time of the whole procedure was found to be roughly 5 minutes per 30 minutes ECG data file, since computation of the HOS parameters, which accounts for the 95% of the overall computational effort, is almost negligible due to employment of HOS estimation for zero lags only.

VI. CONCLUSION

The HOS-RWD, a higher-order statistics-based R-wave detector, used in this study proved to be a very efficient tool for accurate identification of R-wave sequence in ECG recordings. Quantitative and qualitative analysis of the results obtained from the analysis of ECGs from the MIT/BIH ECG database show very reliable and accurate performance. The proposed method is neither depended on subjective human judgment nor affected by noise contamination of the ECG data and could be implemented in a fast and easy way, with low computational cost, allowing its realization in a real time context for clinical heart rate screening.

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